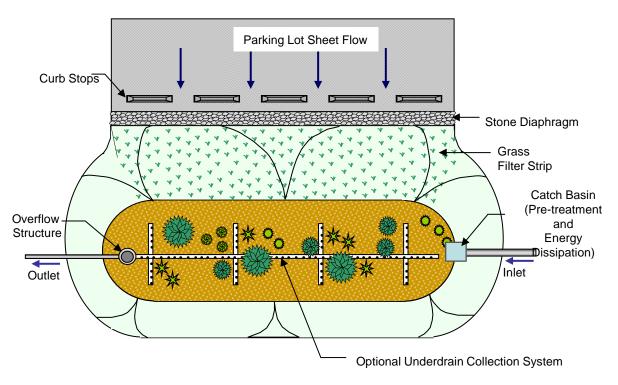
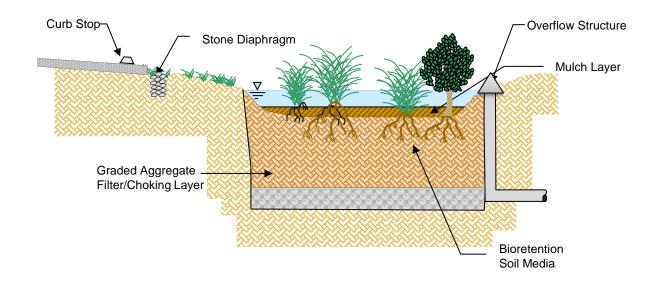


Plan View

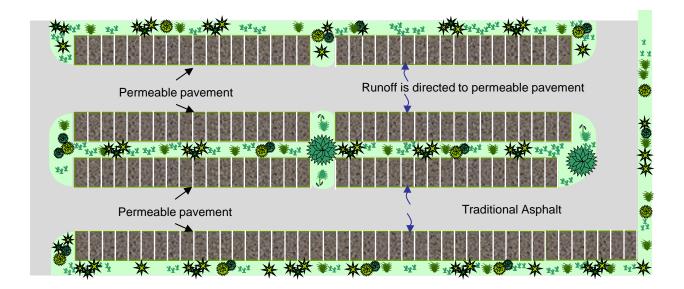


Profile

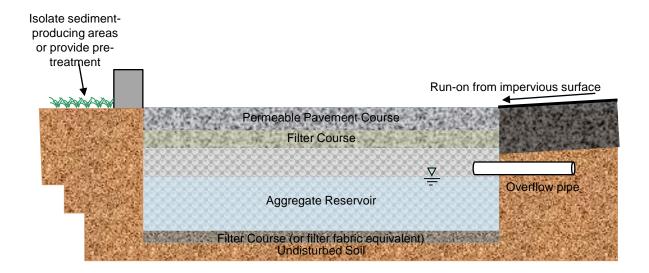


Conceptual Illustration of a Bioretention Facility Cannon Road Water Quality Technical Report Geosyntec Figure consultants Oakland April 2015

Plan View



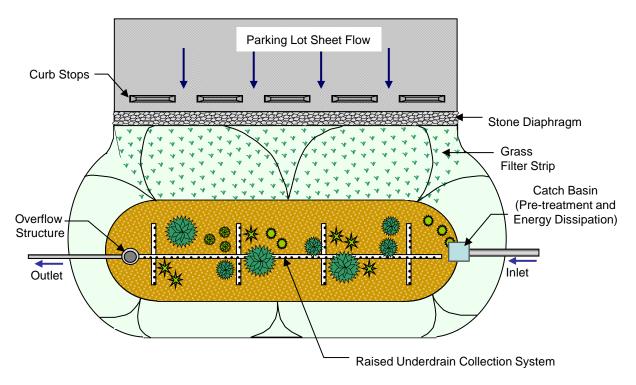
Profile



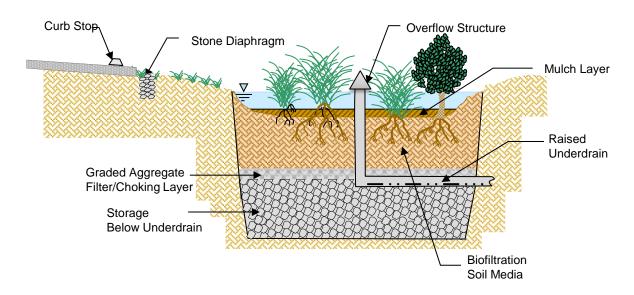


Conceptual Illustration of Permeable

Plan View



Profile



Conceptual Illustration of a Biofiltration Facility with Partial Retention Cannon Road Water Quality Technical Report

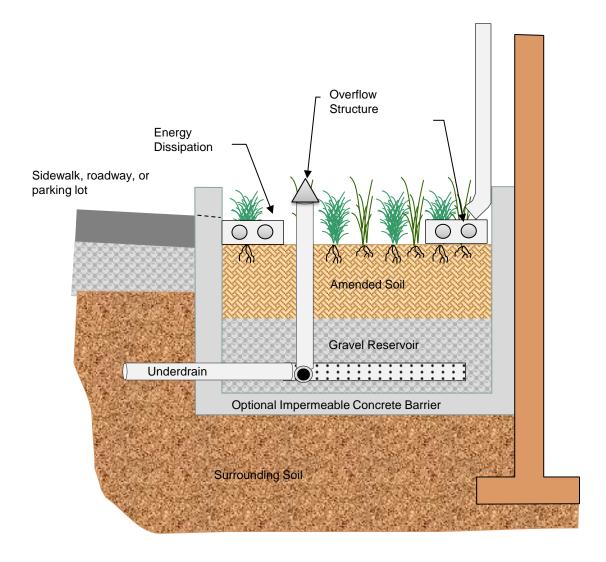
Carrion Road Water Quality Technical Report

Geosyntec consultants
Oakland April 2015

Figure

8

Profile



Conceptual Illustration of Biofiltration (Planter Box)

Cannon Road Water Quality Technical Report

Geosyntec • consultants

Figure

Oakland

9 April 2015

APPENDIX A

Water Quality Modeling Parameters & Methodology

APPENDIX A. WATER QUALITY MODEL METHODOLOGY

A.1. <u>Model Description</u>

A.1.1. Model Overview

The model used to assess stormwater quality impacts associated with the Agua Hedionda South Shore Specific Plan for 85% Open Space and 15% Retail (Specific Plan) is an empirical, volume-based pollutant loads model. This type of loadings model is generally applicable in the planning and evaluation stages of a project. The model was developed to assess the potential impact of development on water quality and to evaluate the effectiveness of the structural Best Management Practices (BMPs) that will treat stormwater runoff as part of the Specific Plan stormwater treatment system. Two Specific Plan conditions were evaluated with the water quality model:

- 1. Pre-development
- 2. Post-development with BMPs

Measured runoff volumes and water quality characteristics of stormwater are highly variable. To account for this variability, a statistical modeling approach was used to estimate the volume of stormwater, the concentration of pollutants in stormwater, and the overall pollutant load (total mass of pollutants) in stormwater runoff. A statistical description of stormwater provides an indication of the average characteristics and variability of the water quality parameters of stormwater, and the probability of compliance with regulatory criteria. It does not forecast runoff characteristics or regulatory compliance for specific storms or monitoring periods.

The statistical model is based on relatively simple expressions describing rainfall/runoff relationships and estimated concentrations in stormwater runoff. The volume of stormwater runoff is estimated using a modification to the Rational Formula, an empirical expression that relates runoff volume to the rainfall depth and the broad basin characteristics. The pollutant concentration in stormwater runoff is represented by an expected average pollutant concentration, called the event mean concentration (EMC). EMCs are estimated from available monitoring data from land use-specific monitoring stations and are considered to be dependent on land use type.

The model does not incorporate the detailed hydraulics or hydrology of the site, which would be more appropriate for design stages and requires additional data and more sophisticated modeling. The model includes water quality benefits achieved by treatment control and low impact development (LID) BMPs, but not source control BMPs, because data is generally not available or is inconclusive for the latter. Model results are presented for average annual runoff volumes, pollutant loads, and pollutant concentrations.

Specific Plan Water Quality Technical Report DRAFT Appendix A

As with all environmental modeling, the precision of results is dependent on how well the hydrologic, water quality and BMP effectiveness data describe the actual site characteristics. Local and regional data used to the fullest extent possible helps to minimize errors in predictions. Model results are presented for average annual runoff volumes, pollutant loads, and pollutant concentrations. The flow chart in Figure A-1 provides an overview of the modeling methodology.

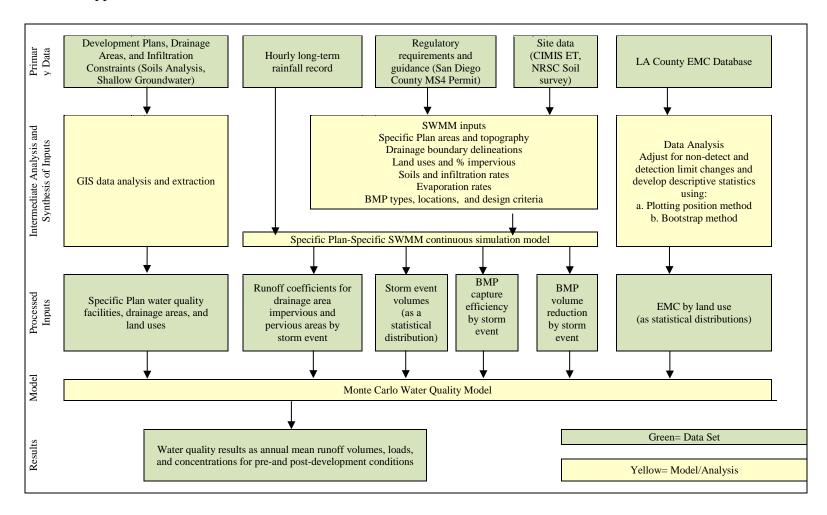


Figure A-1 Overview of Water Quality Analysis Methodology

A.1.2. Technical Basis for Modeling Methodology

A variety of modeling approaches are capable of meeting the technical requirements of this analysis. In general, models can be grouped into three categories:

- Stochastic (or probabilistic): this type of model utilizes observed statistical patterns to produce model estimates. This type of model generally relies on empirical observations, but does not necessarily ignore causal relationships.
- Deterministic (or mechanistic, physically-based): this type of model attempts to perfectly represent physical processes and mechanisms using closed form equations derived from physical phenomena. It is noted that because these models attempt to describe systems that are inherently complex and poorly defined, most deterministic models must rely in part on empirical observations to represent causal relationships.
- Hybrid: this type of model combines elements of stochastic and deterministic models to provide more reliable model estimates.

The modeling methodology used for the Specific Plan incorporates stochastic and empirical elements, and is therefore most accurately described as a hybrid approach. The approach uses an empirical, stochastic water quality estimation approach (Monte Carlo) to produce water quality and pollutant loading estimates. Inputs to this model are derived from empirical sources (Los Angeles County Land Use Monitoring Program) and deterministic modeling of hydrology and hydraulics (EPA SWMM 4.4h). This approach makes use of robust land use and BMP monitoring datasets applicable to the Specific Plan and incorporates important causal relationships in hydrologic and hydraulic response that can be reliably represented with deterministic methods. This approach is believed to be most appropriate to meet the technical requirements of the impact analysis for the Specific Plan-level analysis.

The literature studies summarized below generally support the use of an empirically-based hybrid approach for the type of analysis required for the Specific Plan:

- Obropta et al. (2007) evaluated six deterministic models, three stochastic models, and three hybrid approaches. They concluded that *hybrid approaches show strong potential* for reducing stormwater quality model prediction error and uncertainty [improving the ability to assess] best management practice design, land use change impact assessment [and other applications].
- Charbeneau and Barrett (1998) evaluated different approaches for estimating stormwater pollutant loads based on a comparison of model results to observed land use monitoring data. They found that (1) the development of accurate physically-based models *remains a difficult and elusive goal*, and current understanding of processes *is not sufficient to accurately predict event loads*, (2) a simple empirical stochastic approach is generally as reliable or more reliable than more complicated mechanistic approaches, (3) the use of land use event mean concentrations (EMCs) is appropriate for planning purposes, (4) the

land use EMC approach is most reliable when land use EMCs are used as a stochastic input parameter generated from a probabilistic distribution, and (5) stormwater volume is the single most important variable in predicting pollutant loads.

• The National Research Council's (NRC) 2008 report on *Urban Stormwater Management* in the *United States* generally supports these findings regarding the appropriate use of stormwater quality and quantity models.

As with all environmental modeling, the precision of results is heavily dependent on how well the hydrologic, water quality and BMP effectiveness data describe the actual site characteristics. Local and regional data are used to the fullest extent possible to help minimize errors in predictions, but such data are limited and traditional calibration and verification of the model is not feasible. It is important to note that the predictions of relative differences should be more accurate than absolute values.

A.1.3. Model Assumptions

The water quality modeling methodology requires that some assumptions be made for both the model input parameters and the way the modeling calculations are carried out. Section A.2.6 discusses the assumptions that were made in the development of the model parameters and Section A.3.4 discusses the assumptions inherent in the modeling methodology. Section A.4 discusses the effects of the modeling assumptions on model accuracy.

A.2. Model Input Parameters

Many parameters that can affect pollutant loads and concentrations vary spatially and may not be adequately represented by stormwater monitoring data collected at discrete locations. Examples include source concentrations, topography, soil type, and rainfall characteristics, all of which can influence the buildup and mobilization of pollutants. The following model parameters have been selected based on a review of available data to represent the existing and developed Specific Plan conditions in the water quality model.

A.2.1. Storm Events

A.2.1.1. NCDC Rainfall Gauge Selection

An evaluation of the hourly precipitation records available from the National Climactic Data Center (NCDC) was conducted to identify the rainfall gauge that is most representative for the Specific Plan. The Oceanside Pumping Plant (COOP ID 046379) contains hourly precipitation data over a 50 year period of record (February 1952 through December 2002¹) and is located in San Diego County, CA. Figure A-2 shows the location of the Oceanside Pumping Plant gauge in

¹ Additional records for January 2003 through January 2008 are available; however nearly all of the data from the period are flagged as missing or deleted and do not impact the rainfall record or statistics significantly.

relation to the Specific Plan, located approximately 5 miles away. The gauge elevation of 30 feet above mean sea level (AMSL) is comparable to the Specific Plan elevations of approximately 0-190 ft AMSL, and the gauge location is assumed to have similar rainfall patterns as the Specific Plan due to its proximity to the coastline. The rainfall record has 2.2 percent missing or flagged data over the 50 year period of record. The average annual rainfall depth for the Oceanside Pumping Plant rain gauge is approximately 10.8 inches.



Figure A-2: Location of Oceanside Pumping Plant Rainfall Gage in the Vicinity of the Specific Plan

Rainfall analysis was conducted for two data groups: all storm events; and only the storms that were expected to contribute to stormwater runoff (storms >0.1 inches). The rainfall data were analyzed using a code similar in performance to EPA's Synoptic Rainfall Analysis Program (SYNOP). The customized code (GeoSYNOP) facilitates resolving missing periods of data and is more robust when handling the date and time of storms. GeoSYNOP subdivides the rainfall record into discrete events separated by an inter-event dry period, which in this case was set to a minimum of 6 hours. Small rainfall events, which resulted in rainfall of less than or equal to 0.10

inches, were deleted from the record as such events tend to produce little if any runoff (USEPA, 1989; Schueler, 1987). Storm statistics for the full (all storms) and the trimmed (storms >0.1 inch) data sets are shown in Table A-1.

Table A-1: Precipitation Record Summary by Water Year

Storms	Statistic	Oceanside Gauge
	Average annual rainfall (in):	10.8
	Total number of storms:	1405
A 11 G.	Average number of storms per year ¹ :	27.5
All Storms	Average storm volume (in):	0.39
	Average storm duration (hrs):	7.3
	Average storm intensity (in/hr):	0.089
	Average annual rainfall (in):	10.8
	Total number of storms:	822
Storms >0.1	Average number of storms per year ¹ :	16.1
inch	Average storm volume (in):	0.61
	Average storm duration (hrs):	11.1
	Average storm intensity (in/hr):	0.232

¹ Defined using an inter-event time of 6 hours and obtained using GeoSYNOP analyses described in Section A.2.1.1.

A.2.2. Runoff Coefficients

The long term runoff coefficient (i.e. the fraction of precipitation that runs off as stormwater) is dependent on a number of factors, the most significant being catchment imperviousness. However, for pervious areas, soil characteristics, watershed slope, precipitation patterns, evapotranspiration rates and a variety of other factors also influence runoff coefficient. Runoff coefficients are expected to vary from storm event to storm event as a function of antecedent conditions, storm intensity distribution, storm duration, and storm depth. The following describes how runoff coefficients were estimated for use in the water quality model.

A.2.2.1. SWMM Runoff Coefficient Modeling Parameters

The water quality model uses a modification of the Rational Method, consistent with the San Diego County Hydrology Manual, to estimate a runoff coefficient for sub-basins as a function of the percent impervious for a given storm event. The format of this equation is described as:

$$C = C_i * i + C_p * (1-i)$$

Where:

C = composite runoff coefficient

 C_i = runoff coefficient from impervious areas

 C_p = runoff coefficient from pervious areas

Specific Plan Water Quality Technical Report DRAFT Appendix A

i = imperviousness fraction (ranges from 0 to 1)

Various references provide estimated values for Ci and Cp. The San Diego County Hydrology Manual specifies C_i as 0.90 and bases the determination of C_p on underlying soil type and land use. However, because the pervious and impervious runoff coefficients that make up the runoff coefficient equation are dependent on many site-specific parameters, the runoff coefficient equation used in modeling was estimated using information particular to the Specific Plan. It is recognized that C_p for smaller storms may be zero, while for larger storms it may greatly exceed the long-term average. Thus, the water quality model was developed based on estimates of the Specific Plan pervious area runoff coefficients on a storm-by-storm basis, using a robust method that accounts for more detailed hydrologic processes and antecedent conditions. This method considered the range of conditions that occur and could occur within the Specific Plan and selected appropriately conservative values to account for uncertainty.

Continuous simulation modeling, using the Storm Water Management Model (SWMM), was conducted for the Specific Plan to generate appropriate storm-by-storm pervious and impervious runoff coefficients to use in the runoff coefficient equation for each storm event. A modified version of SWMM 4.4h was used that segregates continuous precipitation records (discussed above) into storm events, tracks the fate of precipitation to losses (i.e. infiltration, evapotranspiration) and runoff for each storm, and tabulates runoff coefficients by storm event.

Assumed flow path lengths were changed between undeveloped areas (areas where no development is expected in the proposed condition and no treatment is required) and post-construction conditions for areas proposed for development. The undeveloped areas retained the same parameters in the existing and developed model conditions. For areas proposed for development, flow path length and hydraulic conductivity were changed from the existing non-developed condition model to the proposed developed condition to reflect changes (i.e. soil compaction, etc.) due to development². The majority of the SWMM modeling parameters assumed for this analysis are shown in Table A-2.

have occurred.

A-8

² Existing development areas in the existing condition are represented in the model with reduced hydraulic conductivities in both the existing and proposed conditions to reflect compaction from the natural condition that may

Table A-2: SWMM Version 4.4h Runoff Module Parameters

Parameter	Unit	Value	Source/Rationale
Routing Method		Kinematic Wave	
Reporting Time Step	Minutes	60	
Dry Weather Time Step	Minutes	240	
Wet Weather Time Step	Minutes	15	
Routing Time Step	Seconds	60	
Flow Path Length	Feet	500 (Existing non- developed condition; Proposed condition outside of development footprint)	Represents typical overland flow path lengths, not a very sensitive parameter
		250 (Proposed developed condition; development footprint)	Represents typical overland flow path lengths, not a very sensitive parameter
Slope (Developed Area)	%	2	Approximate average slopes based on review of topography
Slope (Undeveloped Area)	%	8	Approximate average slopes based on review of topography
Manning's N, Impervious		0.01	Best professional judgment.
Manning's N, Pervious		0.25	Median value for vegetated cover (James, 2002)
Depression Storage, Impervious	Inches	0.02	Estimated value for graveled surface (James, 2002)
Depression Storage, Pervious	Inches	0.06	Best professional judgment.
Infiltration	Method	Green Ampt, see parameters in Table A-4	See Table A-4
Groundwater	-	Not simulated	
Snowmelt	-	Not simulated	

A unit analysis was performed to determine pervious runoff coefficients for the developed and undeveloped areas within the Specific Plan. The proposed developed and undeveloped areas were first divided into three sub-catchments in the SWMM input files by hydrologic soil group (HSG) (HSG B, C, and D). The HSG-specific sub-catchment areas were determined based on watershed-specific soils distributions obtained from the Natural Resources Conservation Service (NRCS) Soil Survey of San Diego County (NRCS, 2013). Using a post-processing engine, SWMM output file runoff results were weighted by development type (i.e. HSG) area distribution and combined to obtain a composite pervious area runoff coefficient for the

development areas for each storm event. The soils distributions assumed for this modeling effort are shown in Table A-3.

Table A-3: Soils Distribution by Development Area Type

Development Area Type	Percent HSG B	Percent HSG C	Percent HSG D		
Undeveloped Area	21%	19%	60%		
Developed Area	88%	2%	10%		

Soils in the Specific Plan will exhibit a range of infiltrative capacity, depending on soil type and condition. Soil type or group can be used to estimate a typical range in soil parameters, such as the Green-Ampt parameters, while soil condition (pre- or post-development) may be used to select the most appropriate parameters within the range. Hydrologic soil groups (HSG) and soil texture classes provided in the Soil Survey were used to classify soils in the Specific Plan into the three soil groups shown in Table A-3 above (B, C, and D) and assign typical ranges of soil parameters to these soil groups. Green-Ampt suction head, saturated hydraulic conductivities and initial moisture deficit values for each HSG were based on the soil texture class reported by the NRCS soil survey for the dominant texture class within the respective HSGs (Table A-4). It has been assumed that compaction during construction will reduce the hydraulic conductivity by 25% in the post-development condition in areas where construction is planned and that a 25% reduction in the pre-development condition exists where there has already been development. While localized effects of incidental compaction may be greater, this assumption is believed to represent a reasonable estimate of drainage basin-wide reduction in long term infiltration rate considering that not all pervious areas will be subjected to incidental compaction. Additionally, vegetation and other natural process tend to restore infiltration rates with time.

Table A-4: Green-Ampt Soil Parameters

Hydrologic Soil Group	Prevalent Soil Texture Class	Suction Head ¹	Saturate Conductivi Undeveloped	IMD ¹ (in/in)	
		(in)	Condition ¹	Developed Condition ²	()
В	Marina Loamy Coarse Sand	8	0.23	0.17	0.30
С	Gravelly Loamy Sand	8	0.10	0.075	0.29
D	Loamy Fine Sand, Terrace Escarpments, Tidal Flats ³	12	0.025	0.019	0.05

¹ Estimated based on texture class from Rawls, et al., (1983).

² Determined based on an assumption of 25% reduction of conductivity due to compaction.

³ Terrace Escarpments and Tidal Flats were not assigned HSGs in the NRCS Soil Survey; properties assumed to be similar to Group D soils.

Reference ET values for estimating actual ET rates was taken from Figure A-3, produced by the California Department of Water Resources. The Specific Plan is located in Zone 1. Reference ET values for Zone 1 are reproduced in Table A-5.

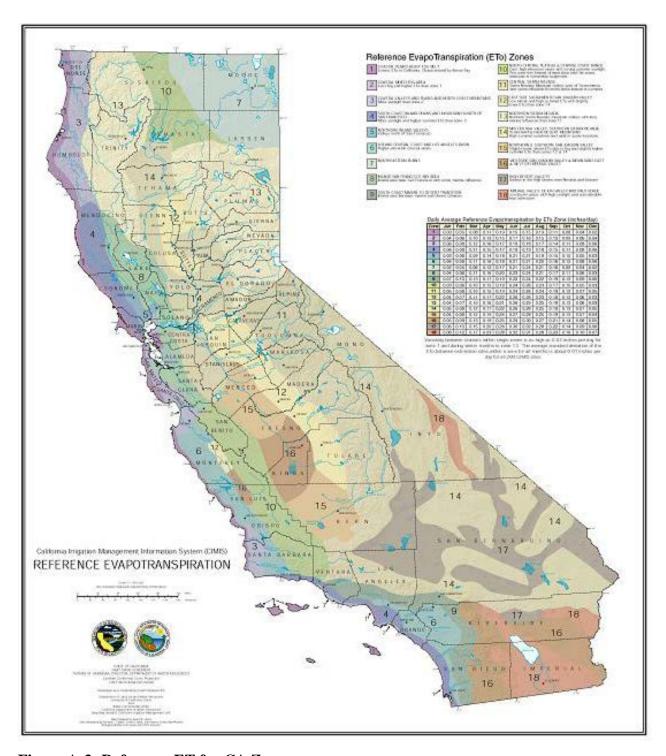


Figure A-3: Reference ET for CA Zones

The existing site land use can be described as row crop agricultural land. A scaling factor of 0.60 was applied to the reference ET values to represent semi-arid vegetation, dry crops and bare soil that are typical of the existing agriculture. This scaling factor can also be used to simulate the landscaped areas and agricultural areas in the post-development condition, which will generally be planted with predominantly drought-tolerant vegetation.

Table A-5: Evaporation Parameters for Hydrology Model (from CA ETo map)

Month	Evapotransp	iration Rates	60%			
Month	inch / month	days / month	inch / month	inch / day		
January	0.93	31	0.56	0.018		
February	1.40	28	0.84	0.030		
March	2.48	31	1.49	0.048		
April	3.30	30	1.98	0.066		
May	4.03	31	2.42	0.078		
June	4.50	30	2.70	0.090		
July	4.65	31	2.79	0.090		
August	4.03	31	2.42	0.078		
September	3.30	30	1.98	0.066		
October	2.48	31	1.49	0.048		
November	1.20	30	0.72	0.024		
December	0.62	31	0.37	0.012		
Total (year)	32.92	365	19.75			

SWMM Runoff Coefficient Results

Using the SWMM inputs and methodology explained above, pervious and impervious runoff coefficients for each storm event were developed. The long-term average runoff coefficients estimated for each drainage area type are shown in Table A-6 for comparison purposes only. Event-by-event runoff coefficients were used for the Monte Carlo statistical model.

Table A-6: SWMM Runoff Coefficients for Watershed Areas

Development	Impervious Ru	noff Coefficient	Pervious Runoff Coefficient				
	San Diego County	Model	San Diego County	Model Methodology			
Category	Hydrology Methodology Manual ¹		Hydrology Manual ¹	Existing ² Proposed			
Undeveloped Area	90	96	20-35 ³	28			
Developed Area	90	96	20-35 ³	5	6		

¹ Included for comparison purposes; only includes storms that would produce runoff, i.e. those >0.1".

As is evident from Table A-6, the average runoff coefficients for impervious areas calculated used in the model are similar to the runoff coefficient calculated using the San Diego County Hydrology Manual method. The pervious runoff calculations estimated using the model methodology for the undeveloped area (existing and proposed) are lower than the runoff coefficients reported to open space in the San Diego County Hydrology Manual. However, the open space coefficients reported in the hydrology manual are representative of "Rural" land uses with a reduction of 0.10 to account for pervious areas (Hill, 2002). A more representative comparison for the undeveloped area runoff coefficients is for "Heavy soil lawn, >7 percent slope", which has a runoff coefficient range of 0.25-0.35 (Hill, 2002). A representative comparison for the developed area runoff coefficients is "Sandy soil lawn, 2 percent slope", which as a runoff coefficient range of 0.05-0.10 (Hill, 2002).

A.2.3. Land Use

The delineation of land uses and areas within the Specific Plan were determined from land use summarized in the Proposed Land Use Plan, 2015 (DUDEK, 2015a) and subsequent GIS analysis for the developed Specific Plan condition. An additional 10 acres of Visitor Serving Commercial (VSC) was added to the area from the Proposed Land Use Plan to account for access roads and other related improvements that have not been specifically sited. The existing condition land use determined by Dudek and consists of fallow agriculture, intensive agriculture, commercial, open space and roadways (DUDEK, 2015b). Existing and developed areas and land use representations for the Specific Plan are summarized in Table A-7. The modeled land uses were based on the most representative land use within the available data sets (see Section A.2.4).

² Includes areas that are not treated and remain unchanged from existing to proposed conditions.

 $^{^{3}}$ Range represents variability in runoff coefficients for permanent open space (HSG A = 20 to HSG D = 35).

Table A-7: Modeled Land Uses and Percent Imperviousness

Land Use Description	Area (Acres)	Imperviousness	EMC Model Land Use							
	Existing Land Uses									
Fallow Crop Residue Poor Cover	59.0	0%	Agriculture							
Narrowleaf Chaparral Fair	81.1	0%	Vacant							
Row Crops	63.3	0%	Agriculture							
Total	203.4	0%								
	Proposed L	and Uses								
Exclusive Agricultural Open Space Lands (EAG- OS)	51.5	0%	Agriculture							
Habitat Management Plan/Coastal Commission Open Space lands (HMP- CC-OS)	75.8	0%	Vacant							
Passive Open Space Lands (P-OS)	39.5	0%	Vacant							
Visitor-Serving Commercial (VSC)	36.7	85%	Commercial							
Total	203.4	15%								

A.2.4. Stormwater Runoff Pollutant Concentrations

Stormwater monitoring data collected by the Los Angeles Department of Public Works (LACDPW) was used to derive estimates of pollutant concentrations in runoff from urban land uses. Stormwater monitoring data collected by Ventura County was used to estimate stormwater pollutant concentrations for agricultural land use.

A.2.4.1. Los Angeles County Monitoring Data

Recent and regional land-use based stormwater quality monitoring data was collected through the LA County Stormwater Monitoring Program. This program was initiated with the goal of providing technical data and information to support effective watershed stormwater quality management programs in Los Angeles County. Specific objectives of this project included monitoring and assessing pollutant concentrations from specific land uses and watershed areas. In order to achieve this objective, the County undertook an extensive stormwater sampling project that included 8 land use stations and 5 mass emission stations (located at the mouths of major streams and rivers), which were tested for 82 water quality constituents. These data are presented in Los Angeles County 1994-2000 Integrated Receiving Water Impacts Report, 2000 and Los Angeles County 2000-2001 Stormwater Monitoring Report, 2001.

Stormwater quality for the Specific Plan was estimated based on the recent EMC data collected by LA County (LA County, 2000 and 2001). These data were used because of their relative proximity to the Specific Plan location and because the monitored land uses provide a relatively good representation of the proposed land uses for the Specific Plan. The monitored land uses stations are listed in Table A-8 with a brief description of the site and when the monitoring data were collected.

Table A-8: LA County Land Use Monitoring Stations Available for Water Quality Modeling

Station Name	#	Modeled Land Use	Site Description ¹	Years Monitoring Conducted
Santa Monica Pier	S08	Commercial	The monitoring site is located near intersection of Appian Way and Moss Avenue in Santa Monica. The storm drain discharges below the Santa Monica Pier. Drainage area is approximately 81 acres. The Santa Monica Mall and Third St. Promenade dominate the watershed with remaining land uses consisting of office buildings, small shops, restaurants, hotels and high-density apartments.	1995-1999
Sawpit Creek	S11	Open Space (& Parks)	Located in Los Angeles River watershed in City of Monrovia. The monitoring station is Sawpit Creek, downstream of Monrovia Creek. Sawpit Creek is a natural watercourse at this location. Drainage area is approximately 3300 acres.	1995-2001
Project 620	S18	Single Family Residential	Located in the Los Angeles River watershed in the City of Glendale. The monitoring station is at the intersection of Glenwood Road and Cleveland Avenue. Land use is predominantly high-density, single-family residential. Drainage area is approximately 120 acres.	1995-2001
Project 1202	S24	Light Industrial	Located in the Dominguez Channel/Los Angeles Harbor Watershed in the City of Carson. The monitoring station is near the intersection of Wilmington Avenue and 220th Street. The overall watershed land use is predominantly industrial.	1995-2001
Dominguez Channel	S23	Freeway (Roadways)	Located within the Dominguez Channel/Los Angeles Harbor watershed in Lennox, near LAX. The monitoring station is near the intersection of 116 th Street and Isis Avenue. Land use is predominantly transportation and includes areas of LAX and Interstate 105.	1995-2001

Station Name	#	Modeled Land Use	Site Description ¹	Years Monitoring Conducted
Project 474	S25	Education (Schools)	Located in Los Angeles River watershed in the Northridge section of the City of Los Angeles. The monitoring station is located along Lindley Avenue, one block south of Nordoff Street. The station monitors runoff from the California State University of Northridge. Drainage area is approximately 262 acres.	1997-2001
Project 404	S26	Multi-Family Residential	Located in Los Angeles River watershed in City of Arcadia. The monitoring station is located along Duarte Road, between Holly Ave and La Cadena Ave. Drainage area is approximately 214 acres.	1997-2001

1 Los Angeles County 1999-2000 Draft Stormwater Monitoring Report (Los Angeles County, 2000)

A.2.4.2. Ventura County Monitoring Data

As part of its NPDES permit, the Ventura County Flood Control District conducts monitoring to determine the water quality of stormwater runoff from areas with specific land uses. One monitoring station, Wood Road at Revolon Slough (site A-1), drains the approximately 350 acre Oxnard Agricultural Plain, which is comprised almost entirely of agricultural land (primarily row crops), including a small number of farm residences and ancillary farm facilities for equipment maintenance and storage. Data from the Wood Road station was used to estimate pollutant concentrations in stormwater runoff for agricultural land use.

Land use runoff sampling for the Ventura County stormwater monitoring program originally began during the 1992/93 monitoring season, with up to several samples collected at each site during each storm season. For the A-1 site, the period of record begins during the 1996/97 storm season, and continues through the present. Data through 2008 were available at the time of preparation of this report. All land use monitoring sites are equipped with automated monitoring equipment, including flowmeters (with area-velocity probes and level sensors) and refrigerated auto-samplers which enable the collection of flow-weighted composite samples. Stormwater quality monitoring data for the agricultural land use site was provided by the Ventura County Watershed Protection District.

A.2.4.3. Data Analysis for Derivation of Land Use EMCs

The Los Angeles County Department of Public Works (LACDPW) monitored stormwater runoff quality from various land uses throughout the County on an annual basis beginning in 1995 through 2001. For each year of monitoring several storm event mean concentrations (EMCs) are reported and included in the County's annual water quality report to the Los Angeles Regional Water Quality Control Board. The convention for dealing with the censored data (e.g., data only known to be below the analytical detection limit) is to substitute half of the detection limit for all

non-detects. L.A. County has followed this convention when providing summary arithmetic statistics of the stormwater monitoring data. This method tends to introduce bias into the estimate of the mean and standard deviation and the summary statistics are not believed to be robust or adequately account for non-detects. To further complicate matters, the detection limit for dissolved copper and total lead has changed during the period stormwater monitoring was conducted by LACDPW.

In an effort to provide more reliable and accurate estimates of land use EMCs for the Specific Plan water quality modeling, a robust method of estimating descriptive statistics for censored data with multiple detection limits was employed. The plotting position method described in Helsel and Cohn (1988) was used to estimate censored values using the distribution of uncensored values. Descriptive statistics were then estimated using the parametric bootstrap method suggested by Singh, Singh, and Engelhardt (1997).

The final land use EMC input parameters developed for the Monte Carlo water quality model include the log-normal mean and log-normal standard deviation. Analyses demonstrate that nearly all of the Los Angeles County land use data sets can be more closely represented by the log-normal distribution than the normal distribution³, which is consistent with findings by Pitt et al. (2004) based on analyses of the NSQD. Table A-10 summarizes the number of data points and the percent non-detects for the pollutants and land uses of interest that have sufficient data available for modeling based on the Los Angeles County data set. While data may be available to develop descriptive statistics for other pollutants (e.g., organics, other metal constituents, trash), reliable land use EMCs statistics could not be computed due to statistically insufficient number of detected results or due to the use sampling techniques not amenable to estimating representative EMCs (e.g., catch basin clean-outs in the case of trash). Also, the availability of BMP effluent quality data similarly limits the number of pollutants that can be effectively modeled; i.e., other pollutants (e.g., organics, other metal constituents) may have land use EMC data available but not BMP effluent data.

A.2.4.4. Example Data Set

To illustrate the statistical methods used to obtain land use EMCs, the LACDPW stormwater monitoring data collected for total lead from the transportation land use station is used. The data were collected from 01/1996 to 04/2001. At the beginning of March 1997 the detection limit for total lead changed from 10 to 5 μ g/L. Table A-9 describes the data according to the number of censored and uncensored values in the example data set.

³ Statistical distribution test results reported by Los Angeles County also confirm this assessment, as summarized by Table 4-14 found at http://LACDPW.org/wmd/npdes/Introport/Tables/Table-4-14.pdf.

Table A-9: Number of Censored and Uncensored Data Points in the Total Lead Transportation Land Use Data Set

Total Lead EMC Data for Transportation Land Use							
Uncensored	37						
Censored < 10 μg/L	2						
Censored < 5 μg/L	38						
Total Data Count	77						

Prior to applying the plotting position method, it is necessary to check the normality of the data. Figure A-4 shows histograms and probability plots of the transportation land use total lead data above detection limits in normal and lognormal space. As indicated in the figure, the data tends to follow a lognormal distribution, a finding that is common with many pollutants in stormwater.

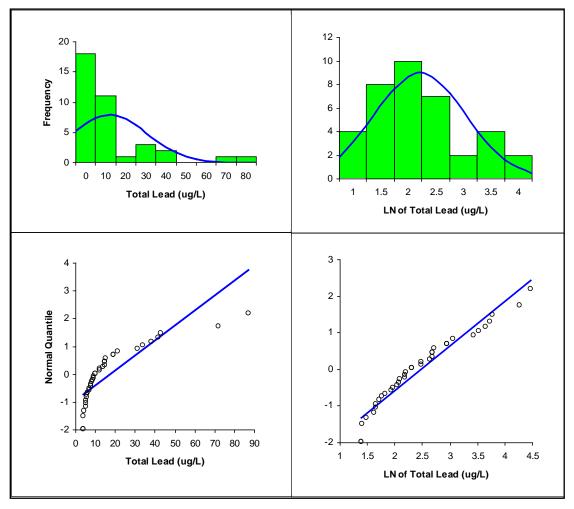


Figure A-4: Histograms and Probability Plots of Transportation Total Lead Data in Arithmetic and Lognormal Space

To verify the visual check that the data are lognormally distributed, the Shapiro-Wilk goodness-of-fit test was used (Royston, 1992). In this test, if p > 0.1, the null hypothesis that the log data follow a normal distribution cannot be rejected. For this example data set, the p-value of the log-transformed uncensored data is 0.293, which indicates that lognormal distribution is a good approximation of the distribution of the data set.

Method for Dealing with Multiple Detection Limits

To account for the multiple detection limits in the censored data sets, a regression on order statistics (ROS) method was employed. ROS is a category of robust methods for estimating descriptive statistics of censored data sets that utilize the normal scores for the order statistics (Shumway et al. 2002). The plotting position method by Hirsch and Stendinger (1987) (summarized by Helsel and Cohn, 1988) was the ROS method used. In this method, plotting positions are based on conditional probabilities and ranks, where the ranks of the censored (below detection) and uncensored data (above detection) related to each detection limit are ranked independently. The method is summarized in the equations below.

After plotting positions for the censored and uncensored values have been calculated, the uncensored values are plotted against the z-statistic corresponding to the plotting position and the best-fit line of the known data points is derived. Using this line and the plotting positions for the uncensored data, the values for the uncensored data are extrapolated. Figure A-5 illustrates the results of the application of the plotting position method on the total lead data for transportation land use.

$$pe_{j} = pe_{j+1} + \frac{A_{j}}{(A_{j} + B_{j})} \times (1 - pe_{j+1})$$
 (1)

Where:

 A_j = the number of uncensored observations above the j detection limit and below the j+1 detection limit.

B_j = the number of censored and uncensored observations less than or equal to the j detection limit.

pe_j = the probability of exceeding the j threshold for j = m, m-1, ... 2, 1 where m is the number of thresholds; by convention $pe_{m+1} = 0$.

Equation 2 was used for plotting the uncensored data and equation 3 was used for plotting the censored data; the plotting positions of the data were calculated using the Weibull plotting position formula.

$$p(i) = (1 - pe_j) + \frac{(pe_j - pe_{j+1}) \times r}{(A_j + 1)}$$

$$(2)$$

Where:

p(i) = the plotting position of the uncensored i data point.

r = the rank of the i^{th} observation of the A_j observations above the j detection limit.

$$pc(i) = \frac{\left(1 - pe_j\right) \times r}{\left(n_j + 1\right)} \tag{3}$$

Where:

pc(i) = the plotting position of the censored i data point.

R = the rank of the i^{th} observation of the n_j censored values below the j detection limit.

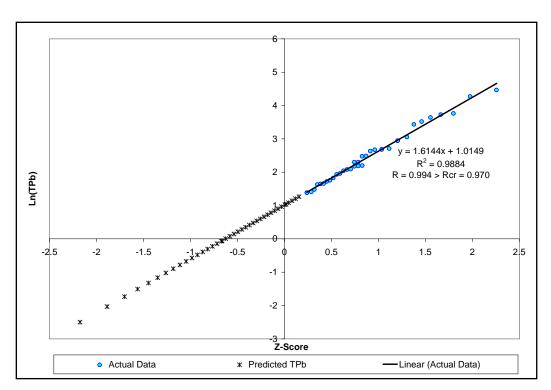


Figure A-5: Probability Plot of the Uncensored and Predicted (Censored) Total Lead Transportation EMCs

Method for Calculating Descriptive Statistics

After the censored data are estimated (or for datasets without non-detects), descriptive statistics were computed using the bootstrap method (Singh et al. 1997). The bootstrap method samples from the data set with replacement several thousand times and calculates the desired descriptive statistics from the sampled data. The steps of the bootstrap estimation method are described below.

1. Take a sample of size n with replacement (the sampled data point remains in the data set for subsequent sampling) from the existing data set (Singh et al. recommends n be the same size as the original data set, this recommendation was followed for the analysis) and compute the descriptive statistic, θ_i , from the sampled data.

- 2. Repeat Step 1 independently N times (20,000 for this analysis) each time calculating a new estimate for θ_i .
- 3. Calculate the bootstrap estimate θ_B by averaging the θ_i 's for i=1 to N.

Fundamentally, the bootstrap procedure is based on the Central Limit Theorem (CLT), which suggests that even when the underlying population distribution is non-normal, averaging produces a distribution more closely approximated with normal distribution than the sampled distribution (Devore 1995). Figure A-6 compares the total lead data after estimating censored values using the ROS method described prior to applying the bootstrap method with bootstrapped means of the ROS data. Note the bootstrap means are more normally distributed than the original data and the central tendency of the data is centered near $8 \mu g/L$.

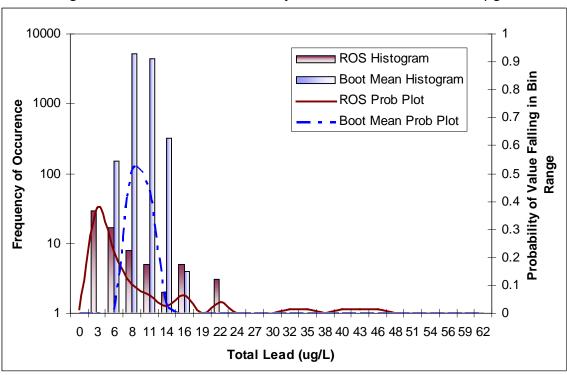


Figure A-6: Comparison of the Distribution of ROS Method Total Lead Data and the Bootstrap Means of the ROS Data.

The majority of the LACDPW stormwater monitoring for the pollutant land use combinations analyzed fit a lognormal distribution. The data that did not statistically fit the lognormal distribution were more closely approximated with a lognormal distribution than a normal distribution. The bootstrap method was applied differently depending on the distributional fit of the data.

If the pollutant EMC data for a particular land use fit a lognormal distribution according to the Shapiro-Wilk goodness-of-fit test, the log-transformed data were bootstrapped and an estimate of the mean and standard deviation were obtained in log space and then converted to arithmetic

Specific Plan Water Quality Technical Report DRAFT Appendix A

space. The assumption of lognormality was more stringently applied than normal by using an alpha significance value of 0.1. This was done to improve the estimate of the standard deviation when the hypothesis of lognormality is rejected. When analyzing data in log space there is a tendency to overestimate the standard deviation for relatively symmetric data and underestimate the standard deviation for severely skewed data. For datasets that did not fit the lognormal distribution, the raw data were bootstrapped to obtain the mean and standard deviation statistics. Bootstrapping the data in arithmetic space assumes no distribution in those instances when a distribution could not be confirmed through goodness-of-fit testing.

Conclusions

The plotting position method for multiple detection limits has been used in conjunction with the bootstrap procedure for calculating the descriptive statistics used to represent pollutant EMC distributions in the water quality model. Table A-10 summarizes the number of data points and detects for the land use specific pollutant EMC data. Table A-11 summarizes lognormal descriptive statistics, and Table A-12 summarizes the resulting arithmetic means. The latter data represent the land use specific pollutant EMCs in the Monte Carlo water quality model.

Table A-10: Summary of Number of Data Points and Percent Non-Detects for Land Use EMC Data.

Land Use		TSS	TP	NH3-N	NO3-N	NO2-N	TKN	DCu	TCu	TPb	DZn	TZn	Cl	TFe	DFe
Commercial	Count	31	32	33	33	7	36	40	40	40	40	40	33	40	39
	% ND	0%	3%	21%	21%	0%	3%	15%	0%	45%	10%	10%	0%	5%	44%
Transportation	Count	75	71	74	75	10	75	77	77	77	77	77	76	77	77
Transportation % ND	% ND	0%	1%	27%	20%	0%	0%	1%	0%	52%	6%	6%	4%	18%	70%
Vacant / Open	Count	48	46	48	50	35	50	52	52	57	52	52	50	52	52
Space	% ND	2%	41%	67%	2%	70%	0%	90%	38%	88%	96%	96%	0%	40%	87%
Agriculture (Ventura County)	Count	24	6	25	23	7	21	25	25	25	25	25 ¹	16	2	2
	% ND	13%	0%	48%	9%	0%	10%	0%	0%	0%	0%	0%1	19%	2	2

¹⁻Total zinc data was insufficient to compute statistics for agriculture in Ventura County; statistics for dissolved zinc were used for total zinc within the model.

2-Total and dissolved iron data was insufficient to compute statistics for agriculture in Ventura County; statistics for vacant/open space were used within the model.

Table A-11: Lognormal Statistics for Modeling Pollutant Concentrations from Land Uses.

Land Use		TSS	TP	NH3	NO3	NO2	TKN	DCu	TCu	TPb	DZn	TZn	Cl	TFe	DFe
Commercial	Mean	4.00	-1.19	-1.08	-0.947	-2.63	0.698	2.25	3.19	1.45	4.87	5.30	3.44	6.47	4.51
	St. Dev	0.634	0.733	1.60	0.832	1.17	1.04	0.723	0.72	1.47	0.575	0.58	0.969	1.45	1.49
Transportation	Mean	3.97	-0.909	-1.71	-0.863	-2.69	0.373	3.24	3.75	1.60	5.10	5.46	1.58	6.39	4.08
	St. Dev	0.878	1.03	1.20	1.06	0.755	0.690	0.693	0.65	1.12	0.776	0.66	0.718	1.14	1.45
Vacant / Open Space	Mean	3.44	-3.20	-3.18	-0.031	-3.95	-0.354	-1.83	1.43	-0.375	3.24	2.23	1.87	4.76	4.10
	St. Dev	1.97	1.44	1.37	0.615	0.494	0.792	1.59	1.36	1.72	0.438	1.44	0.249	2.02	0.64
Agriculture (Ventura County)	Mean	6.56	0.930	-0.080	2.59	-1.17	1.58	2.64	4.08	2.65	3.06	3.06 ¹	3.93	4.76^{2}	4.10^{2}
	St. Dev	0.654	1.38	0.976	0.654	0.725	0.639	0.863	0.99	1.23	1.03	1.03 ¹	0.926	2.02^{2}	0.64^{2}

¹⁻Total zinc data was insufficient to compute statistics for agriculture in Ventura County; statistics for dissolved zinc were used for total zinc within the model.

Specific Plan Water Quality Technical Report DRAFT Appendix A

2-Total and dissolved iron data was insufficient to compute statistics for agriculture in Ventura County; statistics for vacant/open space were used within the model.

Table A-12: Resulting Arithmetic Means from Lognormal Statistics used for Modeling Pollutant Concentrations¹

Land Use	TSS	TP	NH3	NO3	NO2	TKN	DCu	TCu	TPb	DZn	TZn	Cl	TFe	DFe
Units	mg/L	mg/L	mg/L	mg/L	mg/L	mg/L	μg/L	μg/L	μg/L	μg/L	μg/L	mg/L	μg/L	μg/L
Commercial	67	0.40	0.29	1.21	0.55	3.4	12	31	12	153	237	50	4942	357
Transportation	78	0.68	0.37	0.74	0.09	1.8	32	53	9.2	222	292	6.3	1212	185
Vacant / Open Space	217	0.12	0.11	1.2	0.02	1.0	0.6	11	3.0	28	26	6.7	2725	152
Agriculture (Ventura County)	877	6.59	1.5	17	0.40	6.0	20	97	30	36	36 ²	78	2725 ³	152 ³

¹Calculated from values provided in Table A-13.

²Total zinc data was insufficient to compute statistics for agriculture in Ventura County; statistics for dissolved zinc were used for total zinc within the model.

³Total and dissolved iron data was insufficient to compute statistics for agriculture in Ventura County; statistics for vacant/open space were used within the model.

A.2.5. Treatment Assumptions and Estimate of Treatment BMP Performance Parameters

BMP performance is a function of three factors: (1) the fraction of stormwater runoff receiving treatment (often referred to as percent of runoff captured, or simply percent capture); (2) the pollutant removal achieved in the unit by virtue of infiltration and/or evapotranspiration (generically referred to as volume reduction); and (3) the pollutant removal achieved in the treatment unit by virtue of improved water quality.

Capture efficiency calculations used to estimate results for the individual storms and volume reduction estimates are discussed in Section A.2.5.1, and pollutant removal estimates are described in Section A.2.5.2.

A.2.5.1. BMP Capture Efficiency and Volume Reduction

The developed areas within the Specific Plan are proposed to be treated by distributed biofiltration BMPs, as described in Section 5 of the WQTR. The Monte Carlo model utilizes event-by-event estimates of BMP capture efficiencies and volume reduction to describe the hydrologic and hydraulic performance of the Specific Plan BMPs. The event-based inputs were developed using SWMM simulations, using inputs described above in Table A-2. Results from the SWMM simulations are post-processed in a modified SWMM engine (SWMM 4.4h) to yield capture efficiency and volume reduction for each storm in the record.

The modified SWMM engine tracks rainfall, runoff, and treatment system routing in the context of individual storm events. In the Rain block, storm events are delineated from within the continuous rainfall record using algorithms identical in performance to GeoSYNOP, described herein; depth and start and stop times of each event are recorded. In the Runoff block, the rainfall volume associated with each event is tracked between the volume lost and that which runs off; start and stop times of runoff for each storm are recorded for later use. Volume reduction which occurs in parcel-based BMPs which drain to a regional facility is also accounted for in the Runoff block, as described in subsequent sections. Finally, in the Storage/Treatment block, the runoff volume associated with each storm event is tracked between treated volume, bypassed volume, infiltrated volume and evaporated volume. This constitutes a volume-tracking approach of calculating capture efficiency and volume reduction by storm event.

The result of these algorithms is a capture efficiency and volume reduction for each storm in the period of record. The volume reduction achieved by a BMP is a function of the capture efficiency and the fraction of captured stormwater runoff that is infiltrated, evaporated, or transpired by vegetation.

"Bubble Level Model" Biofiltration BMP Representation

The developed areas within the Specific Plan will be treated in a "bubble level" model that routes all developed areas to one hypothetical biofiltration LID BMP. The exact location and routing for the developed areas to distributed biofiltration LID BMPs within the Specific Plan has not yet been determined, so the "bubble level" model represents the cumulative performance and water quality benefits that will be achieved by all of the Specific Plan BMPs. The model BMP configuration was developed to represent the approximate characteristics of biofiltration BMP configurations that are anticipated to be employed within the Specific Plan. The total area and imperviousness routed to the modeled BMP is provided in Table A-13.

Table A-13: Tributary Area and Imperviousness to Modeled BMP

Tributary to BMP	Area, ac	Imperviousness (%)
Developed Area	42.0	74

The "bubble level" BMP was analyzed as volume-based, or sized to capture and treat the runoff volume produced from the design storm (the 85th percentile, 24-hour storm event). The BMP was designed as a biofiltration BMP with no infiltration; therefore, a biofiltration sizing factor of 1.5 times the design capture volume was used to determine the ultimate biofiltration design capture volume.

The hydraulic representation for the biofiltration BMP was developed in the SWMM Storage/Treatment block based on a standard BMP profile that meets the biofiltration design criteria specified in the Draft 2015 Model BMP Design Manual for the San Diego Region (Geosyntec Consultants and Rick Engineering Company, 2015). The BMP modeling assumptions and hydraulic representations are described in Table A-14 below. These inputs were used to develop capture efficiency and volume reduction estimates for use in water quality modeling; however alternative configurations can be used to achieve comparable results.

Table A-14: BMP Modeling Assumptions and Hydraulic Representations

BMP Parameter						
Storage Volume	Sized for Runoff from 85 th percentile, 24-hour Storm					
Storage volume	Event from Tributary Area					
BMP Type	Biofiltration					
Planning Level	Treatment discharge only; no infiltration modeled					
BMP Configuration	Treatment discharge only, no minitration modeled					
Surface Ponding Drain Time	< 24 hours					
Media Filtration Rate (controls underdrain	5 inches per hour					
discharge)	3 menes per nour					
Height of Underdrain Invert Elevation above	0 ft; no infiltration modeled					

BMP Parameter								
Bottom of BMP								
Aggregate Storage above Underdrain Invert	18 inches							
Aggregate Storage Porosity	0.4 in/in							
Media Depth	18 inches							
Media Available Porosity	0.2 in/in							
Surface Ponding Depth	6 inches							
Ponding Depth Side Slopes	3H:1V							

The storm-by-storm capture efficiency and volume reduction estimated from the BMP simulation was extracted from SWMM model output and used to represent the hydraulic performance of the biofiltration BMP in the Monte Carlo model. Table A-15 reports the long-term hydrologic performance of the BMP (capture efficiency and volume reduction).

Table A-15: BMP Hydraulic Performance

Developed Area	Capture Efficiency	Volume Reduction ¹
Biofiltration BMP	98%	0%

Expressed as a portion of captured water.

A.2.5.2. BMP Pollutant Removal

BMP effluent quality, like land use EMCs, is highly variable. To account for this variability, effluent quality data were analyzed and descriptive statistics were generated by means of a technique similar to that used to generate land use EMCs. The descriptive statistics generated were used as BMP effectiveness inputs to the Monte Carlo model.

The International Stormwater BMP Database (www.bmpdatabase.org) is a comprehensive source of BMP performance information. The BMP Database is comprised of carefully examined data from a peer-reviewed collection of studies that have monitored the effectiveness of a variety of BMPs in treating water quality pollutants for a variety of land use types. Research on characterizing BMP performance suggests that effluent quality rather than percent removal is more reliable in modeling stormwater treatment (Strecker et al. 2001). Schueler (1996) also found in his evaluation of detention basins and stormwater wetlands that BMP performance is often limited by an achievable effluent quality, or "irreducible pollutant concentration;" acknowledging that a practical lower limit exists to which stormwater pollutants can be removed by a given technology. While there is likely a relationship between influent and effluent for some BMPs and some constituent concentrations, the analyses that have been conducted to date do not support flat percent removal values relative to influent quality. As such, the distribution of effluent concentrations of stormwater BMPs reported in the BMP Database are used to estimate BMP performance for water quality modeling of the proposed conditions.

Future studies may support a refinement to the approach of effluent concentration-based BMP performance modeling, such as the development of more complex influent-effluent relationships. However, it should be noted that the stochastic modeling approach accounts for, at least in part, the uncertainty of not knowing the relationship between influent and effluent concentrations since the BMP effluent distributions are based on a variety of BMP studies with a wide-range of influent concentrations, representing a variety of tributary drainage area land use characteristics. Furthermore, the Monte Carlo model employed only accounts for pollutant reductions if the predicted influent is greater than the achievable effluent quality estimated for the modeled BMP (i.e. effluent equals influent [or land use-based] concentrations up until the influent concentration exceeds the effluent concentration). Therefore, influent (or land use EMC-based) concentrations are considered by the model since they are directly used to determine whether or not treatment occurs.

Similar to the estimation of land use EMCs, final BMP effluent values used were determined using a combination of regression-on-order statistics and the "bootstrap" method. Log-normality was assumed for BMP effluent concentrations.

Discharge from the Specific Plan "bubble level" BMP was assumed to have effluent quality equivalent to a 'biofiltration' BMP. 'Biofiltration' effluent values were estimated by combining data from both bioretention-type BMPs and media filters, which utilize similar mechanisms to remove pollutants and are both incorporated into biotreatment BMP design. The data is combined to represent the worse performing mean effluent concentrations achievable by these BMP types. Bioretention, media filter, and the combined 'biofiltration' type BMP effluent values are included in the tables below.

Table A-16 summarizes the number of data points (individual storm events) and percent non-detects for the pollutants and biotreatment BMP types listed above. Table A-17 summarizes the log-normal statistics of the biotreatment BMP types as well as the statistics that were used in the water quality model (representing the lowest performance for each pollutant), and Table A-18 summarizes arithmetic descriptive statistics for those data sets.

BMP effluent concentrations are assumed to be limited by an "irreducible effluent concentration," or a minimum achievable concentration. Lower limits are currently set at the 10th percentile effluent concentration of BMP data in the International BMP Database for each modeled BMP type for which the BMP data show statistically significant differences in influent and effluent means. If the differences are not statistically significant, the 90th percentile is used as the minimum achievable effluent concentration, which essentially assumes no treatment. Table A-19 summarizes the irreducible effluent concentration estimates used by for water quality modeling of the proposed condition.

No treatment was assumed for nitrite (NO_2) , total and dissolved iron, and chloride, and BMP effluent data were not available for total and dissolved iron, so these constituents are not included on the following summary tables even though they were included in the model.

Table A-16: Summary of Number of Data Points and Percent Non-Detects for BMP Effluent Concentration Data from the International BMP Database

BMP		TSS	TP	NH3	NO3	TKN	DCu	TCu	TPb	DZn	TZn
Bioretention	Count	181	232	146	NA	179	34	67	54	NA	110
Dioretention	% ND	11%	6%	19%	NA	3%	6%	10%	74%	NA	29%
Sand Filters	Count	332	325	187	174	314	150	305	291	149	332
Sand Pitters	% ND	10%	10%	28%	3%	9%	9%	14%	31%	26%	15%

Table A-17: International BMP Database Lognormal Statistics of BMP Effluent Concentrations

BMP		TSS	TP	NH3	NO3	TKN	DCu	TCu	TPb	DZn	TZn
Bioretention	Mean	2.223	-1.949	-1.945	NA	-0.022	2.498	2.210	0.740	NA	2.678
Dioretention	St. Dev	1.422	1.544	1.466	NA	1.094	0.682	1.048	1.317	NA	1.375
Sand Filters	Mean	2.166	-2.434	-2.354	-0.748	-0.615	1.257	1.662	0.405	2.089	2.557
Sand Theis	St. Dev	1.308	0.942	1.164	1.102	0.944	1.033	1.036	1.226	1.423	1.315
Biofiltration ¹	Mean	2.223	-1.949	-1.945	-0.748	-0.022	2.498	2.210	0.740	2.089	2.678
Diomitation	St. Dev	1.422	1.544	1.466	1.102	1.094	0.682	1.048	1.317	1.423	1.375

^{1 –} Biofiltration BMPs are represented as the worst performing of Bioretention and Sand Filter categories from the BMP Database for conservatism.

Table A-18: International BMP Database Arithmetic Estimates of BMP Effluent Concentrations

ВМР	ita	TSS	TP	NH3	NO3	TKN	DCu	TCu	TPb	DZn	TZn
DIVIP	units	mg/L	mg/L	mg/L	mg/L	mg/L	ug/L	ug/L	ug/L	ug/L	ug/L
Diametantian	Mean	25.4	0.47	0.42	NA	1.78	15.34	15.78	4.99	NA	37.4
Bioretention	St. Dev	65.1	1.47	1.15	NA	2.71	11.81	22.30	10.79	NA	88.7
Sand Filters	Mean	20.5	0.14	0.19	0.87	0.84	6.00	9.02	3.18	22.2	30.6
Sand Filters	St. Dev	43.6	0.16	0.32	1.34	1.01	8.29	12.52	5.94	57.0	65.9
Biofiltration ¹	Mean	25.4	0.47	0.42	0.87	1.78	15.34	15.78	4.99	22.2	37.4
Diomitation	St. Dev	65.1	1.47	1.15	1.34	2.71	11.81	22.30	10.79	57.0	88.7

1 – Biofiltration BMPs are represented as the worst performing of Bioretention and Sand Filter categories from the BMP Database for conservatism.

Table A-19: International BMP Database Arithmetic Irreducible Effluent Concentration Estimates

BMP	TSS	TP	NH3	NO3	TKN	DCu	TCu	TPb	DZn	TZn
DIVIF	mg/L	mg/L	mg/L	mg/L	mg/L	ug/L	ug/L	ug/L	ug/L	ug/L
Bioretention	1.59	0.028	0.039	NA	0.30	4.79	2.31	0.41	NA	2.12
Sand Filters	1.24	0.022	0.021	0.13	0.18	0.85	1.20	0.30	1.28	2.32
Biofiltration ¹	1.59	0.028	0.039	0.13	0.30	4.79	2.31	0.41	1.28	2.12

^{1 -} Biofiltration BMPs are represented as the worst performing of Bioretention and Sand Filter categories from the BMP Database for conservatism.

A.2.6. Model Parameter Reliability & Assumptions

The input parameters for the water quality model fall into five main categories shown below. Each of the categories of input data is evaluated for accuracy reflecting the Specific Plan site conditions:

- Precipitation data;
- Runoff Coefficients;
- Land Use data;
- Stormwater pollutant EMCs; and
- BMP performance estimates.

A.2.6.1. Precipitation Data

The precipitation record used for the Specific Plan was the Oceanside Pumping Plant NCDC gauge, which is located approximately 5 miles north of the Specific Plan. The gauge elevation of 30 feet AMSL is comparable to the Specific Plan elevations of approximately 0-190 ft AMSL, and the gauge location is assumed to have similar rainfall patterns as the Specific Plan due to its proximity to the coastline.

The San Diego County Hydrology Manual (2003) contains an 85th Percentile Precipitation Isopluvial Map from June 2001 that estimates that the 85th percentile, 24-hour storm event for the Specific Plan is between 0.6 and 0.65 inches. The 85th percentile, 24-hour storm event for the record used for the model is 0.90 inches, which does not include storm events that are not anticipated to produce runoff (<0.1") and is based off of an hourly rainfall record that extends over 50 years. Therefore, the record used in the modeling is considered reliable and representative of the Specific Plan, using the most recent data available.

A.2.6.2. Runoff Coefficients

The estimation of runoff coefficients, described in Section A.2.2, is highly dependent on soil properties (i.e. infiltration potential) and less dependent on parameters such as ET rates, slopes, and depression storage. Soil properties are estimated as accurately as possible from available data such as soil surveys and site-specific geotechnical studies. However, runoff coefficients estimates may somewhat overestimate or underestimate stormwater runoff. The net result on the water quality model is that this parameter is not conservatively estimated; however, it is estimated as accurately as the available information permits.

A.2.6.3. Land Use Data

The land use data for the existing and developed conditions has a high level of accuracy for classifying land use type and maximum area of disturbance. The percent impervious values used in the water quality model for the urban land uses in the developed condition are based upon anticipated development patterns for the land use type. These percent impervious values assigned to types of urban land uses are somewhat conservative to provide a margin of safety

when estimating flow rates for flood control analysis. These same percent impervious values are used for calculating runoff coefficients estimates which results in a conservative estimate of stormwater runoff volumes.

A.2.6.4. Stormwater Pollutant EMCs

Stormwater pollutant EMCs are estimated from monitoring data collected by the LADPW and the Ventura County Flood Control District from land use characterization stations that do not have the same level (if any) of site design and source control BMPs that will be implemented for the Specific Plan. Therefore the stormwater pollutant EMCs estimated from the LADPW and Ventura County data are probably somewhat conservative compared to the pollutant concentrations in stormwater runoff that will occur from the developed conditions of the Specific Plan.

A.2.6.5. BMP Capture Efficiency & Effluent Concentrations

Stormwater capture efficiency estimates were calculated in SWMM to provide results on a storm-by-storm basis for input into the water quality model, to accurately reflect the anticipated performance of the biofiltration BMPs for the Specific Plan. Evapotranspiration and flows out of the BMPs were estimated based on planning level representation of anticipated facility type and geometry. Because specific BMP designs have not been developed, model representations have been developed to approximately represent BMP performance and have tended to err on the side of lower performance where appropriate.

BMP effluent concentrations are based on studies contained in the International Stormwater BMP Database. These studies are screened to remove data for undersized (i.e., inadequate design criteria) BMPs that are likely to have pollutant removal performance substantially less than the BMPs to be constructed for the Specific Plan. This screening is believed to improve the accuracy of BMP performance estimates; however it is only intended to remove BMPs that are clearly unrepresentative in terms of sizing. The screening process is intended to include BMPs with adequate performance that may not be as well designed or maintained as the structural BMPs that will be part of the Specific Plan.

Three specific assumptions tend to introduce considerable conservatism into the modeling results for capture efficiency and treatment performance:

- BMP sizing assumptions used for capture efficiency calculations are based on sizing for water quality treatment only. It is anticipated that some/most of the BMPs may be sized for hydromodification control, which is a larger sizing standard and would tend to result in a significantly higher capture performance. Therefore, the capture efficiency estimates for BMPs are likely considerably understated in this analysis.
- It is assumed that there will be no volume reduction in the BMPs because no infiltration was assumed. There may be some incidental infiltration within the BMPs or partial infiltration if site-specific investigations allow.

 Additionally, the BMP effluent statistics used to model biofiltration represent the lowest performance of the menu of biotreatment BMPs that may be implemented in the Specific Plan. It is anticipated that average biofiltration BMP effluent quality will likely be better than was assumed for modeling purposes.

A.2.6.6. Conclusions

The precipitation data, runoff coefficient, land use type and area, and land use percent imperviousness are thought to be reasonably accurate representations of the site conditions and do not considerably increase the conservativeness of the water quality model. The stormwater pollutant EMC estimates are believed to result in conservative estimates of pollutant concentrations and pollutant loads because they do no account for source control and site design practices that will be implemented by the Specific Plan. The water quality estimates for the developed condition are believed to be moderately conservative (i.e., tend to overestimate loads and concentrations) due to pollutant concentration estimates, and BMP performance estimates that in general do not include the benefits of site design or source control BMPs that are planned to be implemented in the Specific Plan and are based on the lowest performing BMP options between bioretention and sand filters.

A.3. <u>Model Methodology</u>

A Monte Carlo simulation method was used to develop the statistical description for storm water quality. In this approach, the storm water characteristics from a single storm event are first estimated. The storm depth was determined by randomly sampling from the historical storm depth frequency distribution. Similarly, an EMC was determined by randomly sampling from the frequency distribution of EMCs. The precipitation volume and EMC were used to determine runoff volume, pollutant concentration, and pollutant load of the single storm event. BMP volume reduction and performance (effluent quality), determined by randomly sampling from the developed frequency distributions, were used to calculate the pollutant removal resulting from treatment in the BMP system. This procedure was then repeated thousands of times (20,000), recording the volume, EMC and load from each randomly selected storm event, including treatment for the developed condition. The statistics of these recorded results provide a description of the average characteristics and variability of the volume and water quality of storm water runoff.

This method was applied to the Specific Plan using the Specific Plan-specific inputs as described above. The modeled pollutants for the Specific Plan were:

- Total Suspended Solids (sediment)
- Total Phosphorus
- Ammonia
- Nitrate
- Nitrite

- Total Nitrogen⁴
- Dissolved Copper
- Total Copper
- Dissolved Iron⁵
- Total Iron
- Total Lead
- Dissolved Zinc
- Total Zinc
- Chloride

The steps in the Monte Carlo Water Quality Model are as follows:

- 1. Develop a statistical description of the number of storm events per year, and randomly select a number N_{storms} .
- 2. Estimate the volume of storm runoff for each land use area from a randomly selected storm event.
- 3. Randomly select a pollutant concentration in storm runoff for each land-use area and each pollutant.
- 4. Calculate the total runoff volume, pollutant load, and concentration in runoff from the modeled portion of the Specific Plan, for both existing and developed conditions.
- 5. Calculate a total annual pollutant load by repeating steps 2-4 N_{storms} times, where N_{storms} is the number of storms per year, randomly selected in step 1.
- 6. Repeat steps 1 6 a total of 20,000 times for each pollutant modeled, recording the estimated pollutant concentration and annual load for each iteration.
- 7. Develop a statistical representation (mean annual value) of the recorded storm water pollutant loads and concentrations.

Each of the seven steps is described below.

A.3.1. Storms & Stormwater Runoff (Steps 1 & 2)

Step 1 – Statistical Representation of Number of Storm Events per Water Year

Number of Storms per WaterYear

⁴ TKN is modeled, but the results are not reported. Total Nitrogen results are reported from the sum of Nitrate, Nitrite, and TKN.

⁵ Dissolved Iron was modeled with no removal in the BMPs to determine the proportion of Total Iron that is estimated to be dissolved versus particulate.

The number of storm events per water year was calculated for the precipitation record used for the model. The modeled average number of storm events per water year (>0.1 inches, defined using an inter-event time of 6 hours and obtained using GeoSYNOP) and standard deviation for the rainfall record is included in Table A-20 below.

Table A-20: Number of Storm Events¹ per Water Year and Standard Deviation by Record

Rainfall Record	Number of Storm Events ¹ (N)	Standard Deviation (SD)
Oceanside Pumping Plant	15.6	6.6

¹Defined using an inter-event time of 6 hours and obtained using GeoSYNOP analyses.

Figure A-7 illustrates a frequency histogram of the number of storm events per water year at the Oceanside gauge. The number of storm events per water year was modeled with a normal distribution. In the simulation, the number of storms per water year was determined by randomly sampling from the normal distribution and rounding to the nearest whole number, using the equation:

$$N_{storms} = 15.6 + 6.6 R_N$$

where:

 $R_N = a$ standard normal variant with a mean of 0 and a standard deviation of 1.

If the arbitrary number of storms per year was zero or negative, then the normal distribution was re-sampled until a positive number was obtained.

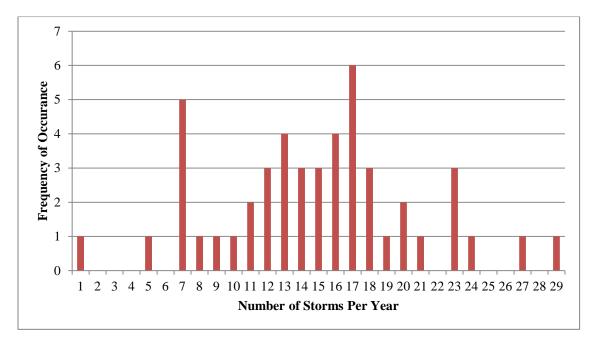


Figure A-7: Distribution of Storms per Water Year at the Oceanside Pumping Plant Gauge

Step 2 – Estimate the Volume of Storm Runoff from a Storm Event.

The runoff volume from each storm was estimated using the following equation:

$$V = R_v P A \qquad (5)$$

where:

V = the stormwater runoff volume (ft³)

P = the precipitation depth of the storm (ft)

A = the drainage area (ft^2)

 R_v = the volumetric runoff coefficient for each storm event, a unit-less value that is a function of the imperviousness of the drainage.

To address runoff from multiple land-use types, the total stormwater runoff volume is determined as the sum of runoff from each land-use type:

$$V_{\text{wshed}} = \sum_{\text{lu}} V_{\text{lu}} = \sum_{\text{lu}} (R_{\text{v lu}} P A_{\text{lu}})$$
 (6)

where lu designates the land-use type. It is assumed that rain falls uniformly over all land-uses.

The steps used to calculate the volume of runoff from a randomly selected storm event were:

Step 2a: Obtain a storm depth by randomly sampling from all storm events in the record.

Step 2b: For each land-use area, calculate a runoff volume using equation (5). The same storm depth is applied to each land-use area.

Step 2c: Sum the runoff volumes from each land-use area to obtain the total runoff from the watershed for a particular storm event with equation (6).

A.3.2. Pollutant Loads & Concentrations (step 3 & 4)

Step 3 – Estimate a Pollutant Concentration in Storm Runoff from Each Land Use Area

Runoff Concentration

The distribution of land use-based pollutant concentration in storm runoff was developed based on the process described in Section A.2.4. For each storm event, stormwater EMCs were sampled randomly for each modeled land use and water quality parameter. The runoff concentration from each land-use area was evaluated with the expression:

$$C_{land-use} = \exp(\mu_{\ln x} + \sigma_{\ln x} R_N) \tag{7}$$

where:

 $\mu_{\ln x}$ = the log-normal mean

 $\sigma_{\ln x}$ = the log-normal standard deviation

 R_N = a standard normal random variable

<u>Step 4 – Calculate the Total Runoff Volume, Pollutant Load, and Pollutant Concentration in a Storm Event</u>

Step 4a: The total runoff volume in the watershed was calculated with equation (6) as discussed in Step 2:

$$V_{wshed} = V_{land-use1} + V_{land-use2} + \dots + V_{land-usei}$$
 (8)

where the same randomly selected storm event was used to calculate runoff volume in each of the land-use areas.

Step 4b: The total pollutant load from the watershed was calculated by:

$$L_{wshed} = V_{land-use1}C_{land-use1} + \dots + V_{land-usei}C_{land-usei}$$
(9)

where the concentration in each individual land-use area was calculated with equation (7) discussed in step 3.

Step 4c: The average pollutant concentration in runoff from the entire watershed from a single storm event was calculated by dividing the total watershed load (Step 4B) by the total watershed runoff volume (Step 4A):

$$C_{wshed} = L_{wshed} / V_{wshed}$$
 (10)

Model steps up to 4C (Eq 10) were used in the model calculations for catchments with and without modeled BMPs. The resulting values from Equation 9 and Equation 10 represent the end model output for catchments without modeled BMPs and represent intermediate calculations for catchments with modeled BMPs

Catchments with treatment BMPs used additional calculations to determine the reduction in pollutant load and concentration achieved with treatment BMPs. The fraction of stormwater runoff receiving treatment was calculated for each storm event, using the capture efficiency associated with that event, as described in Section A.2.5. BMP performance was modeled using a randomly selected effluent concentration achieved within the BMP for each water quality pollutant.

Step 4d: The total pollutant load from watersheds with treatment BMPs was calculated by:

$$L_{wshed_BMPs} = \left[Cap_{\%} \times V_{wshed} \times C_{eff} \times (1 - VR\%) \right] + \left[(1 - Cap_{\%}) \times V_{wshed} \times C_{wshed} \right]$$
(11)

where:

 $Cap_{\%}$ = the volumetric percent capture of the BMP.

 C_{eff} = the randomly determined effluent concentration from the BMP.

VR% = the percent reduction in effluent volume achieved by the BMP (see Section A.2.5.1).

 C_{eff} was determined from sampling from the lognormal distribution described by the parameters contained in Table A-11. V_{wshed} and C_{wshed} were calculated per Steps 4A and 4C, respectively

Step 4e: The average pollutant concentration in runoff from the entire watershed with treatment from a single storm event was calculated by dividing the total watershed load with treatment by the total watershed runoff volume less the volume lost in BMPs:

$$C_{wshed BMPs} = L_{wshed BMPs} / V_{wshed BMPs}$$
 (12)

where:

$$V_{wshed\ BMPs} = V_{wshed} \times \left[1 - \left(Cap_{\%} \times VR\%\right)\right] \tag{13}$$

The results of step 4D (Eq 11) and step 4E (Eq. 12) were used to compute model results for developed conditions with treatment.

Figure A-8 provides a diagrammatic representation of these water quality calculations.

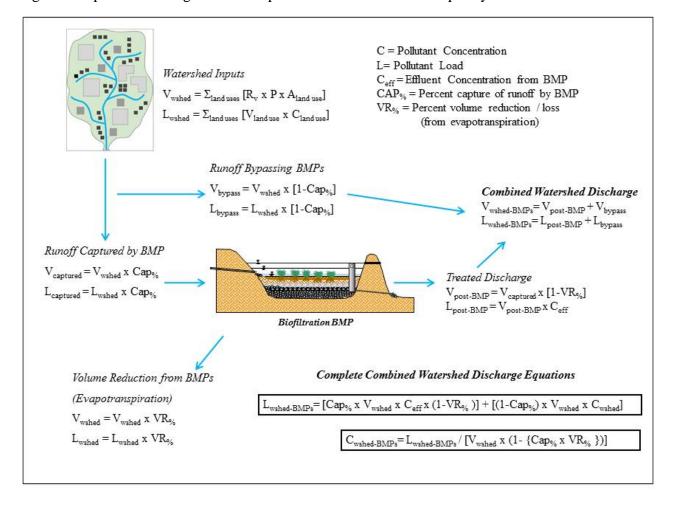


Figure A-8: Monte Carlo Model Schematic

A.3.3. Annual Pollutant Loads, Concentrations, and Distributions (steps 5, 6, & 7)

<u>Step 5 – Calculate a Total Annual Pollutant Load</u>

The annual pollutant load is simply the sum of pollutant loads generated from all storms in a given year, based on the random selection described in Step 1. Therefore, steps 2-4 were repeated N_{storms} times (where N_{storms} was randomly selected per step 1), recording the total pollutant load from each randomly selected storm event. The individual storm loads were summed to obtain the total annual pollutant load.

Step 6 & 7 – Determine Distribution of Storm Concentration and Annual Loads

Steps 1-5 were repeated a total of 20,000 times, recording the pollutant concentration and annual load from each iteration. The resultant distributions can be used to present a frequency distribution for pollutant concentrations or loads using statistics calculated from the 20,000 Monte-Carlo iterations.

A.3.4. Model Methodology Assumptions

The following five key assumptions are made for the Monte Carlo water quality modeling methodology:

- 1. The assumed probability distributions of model parameters;
- 2. The assumption of independence between model parameters (i.e. no correlation between randomly determined variables);
- 3. Assigning a Lower Limit to BMP Effluent Concentrations;
- 4. Limiting pollutant removals to pollutants with data; and
- 5. Modeling structural BMPs to only remove pollutants and not acting as a source.

The implications of each of these assumptions to the water quality projections are discussed below.

1) Distribution Assumptions: Probability distributions are assumed to represent the number of storms per year, stormwater pollutant concentrations, and BMP effluent concentrations. Observed precipitation data (i.e., storm frequency) and stormwater monitoring data are fit with either a normal or lognormal distribution using standard statistical procedures. The values of storms per year, storm depth, runoff pollutant concentration, and BMP effluent concentrations used in given iteration in the Monte Carlo analysis are governed by the selected distributions. Large samples of these estimated variables will approximate the assumed distributions, and will have the same mean and variance that was observed in the precipitation and monitoring data. The following describes the distributions for various input parameters.

Storms per Year: Figure A-7 shows the number of storms per year occurring at the Oceanside gauge. The number of storms occurring per year for the Specific Plan record appears to lie between the normal and lognormal distributions. The normal distribution was used to determine the number of storms per year simulated in the water quality model, as use of the lognormal distribution would overestimate the average annual precipitation, as well as its variability, when the distribution of the data are not heavily skewed.

Stormwater Pollutant Concentrations: The Shapiro-Wilk Test was used to determine the statistical distribution that best represents the raw stormwater runoff monitoring data collected in Los Angeles and Ventura Counties. In most instances the data were found to be log-normally distributed at a confidence level of 0.10. In some instances, the data were not well fit by either the normal or lognormal distributions, but were found to be more closely approximated by the log-normal distribution. For data sets with greater than 50 percent non-detects or that were not log-normally distributed according to the Shapiro-Wilk test, data were analyzed (ROS and bootstrap) in arithmetic space as to not unreasonably overestimate the standard deviation of the data set. Since stormwater pollutant concentrations, in general, tend to be well approximated by the lognormal distribution (Helsel and Hirsh, 2002), the data sets that did not meet the lognormal criterion are still believed to belong to a log-normally distributed population, but the number of data points is too few to statistically confirm that this is the case. Therefore, simulations of stormwater concentrations in the water quality model were still conducted in lognormal space. This assumption is believed to result in a more accurate prediction than would the application of the normal distribution.

BMP Effluent Concentrations: Goodness-of-fit tests have been conducted on the raw BMP effluent monitoring data from the International BMP Database with the Shapiro-Wilk Test. Results of these tests either resulted in (1) confirmation of the appropriateness of the lognormal distribution for the data; or (2) in the instances when the data did not meet the significance criteria of a p value > 0.1, that the data were more closely approximated with the lognormal distribution than the normal. The use of the lognormal distribution to represent BMP effluent concentrations results in higher average estimates of BMP effluent concentration. This is believed to be a more accurate estimation of BMP performance than use of the normal distribution, and is considered a more conservative assumption (leading if anything to higher than anticipated effluent concentrations).

2) <u>Assumption of No Correlation between Model Parameters</u>: The water quality model randomly selects stormwater pollutant concentrations independent of the storm depth or antecedent dry period for each storm event modeled. The validity of the assumption of independence between variables is supported by analyses conducted by Environmental Defense Sciences (2002), who did not find a strong correlation between storm volume and event mean concentrations (EMCs) in the LA County data for the education land-use site. Data analyses for the single family residential land use were found to be weakly correlated (R^2 of 0.6 ± 0.1) for some pollutants with storm depth; however some pollutant showed little correlation between

these variables. Where weak correlations were present, stormwater pollutant concentrations tended to decrease with storm size. Correlations between pollutant concentration and antecedent dry period were similarly variable. For the single family land use, correlations between pollutant concentration and antecedent dry period were moderately significant for a few pollutants (R^2 of 0.8 ± 0.03), and weak for other pollutants. Correlations between pollutant concentration and antecedent dry period varied widely for the educational and multi-family land uses.

The results of these analyses indicated that no consistent level of correlation has been demonstrated between the stormwater EMCs and the storm depth or the antecedent dry period, with weak or no correlation observed for most pollutants and land-uses. On this basis, random selection of stormwater pollutant concentrations, independent of storm depth and antecedent dry period, is warranted for the water quality model.

Effluent concentrations are considered a more reliable estimator of treatment performance than percent removal (Strecker et al. 2001). BMP effluent concentrations were sampled independently of stormwater concentrations (i.e. influent concentration to the BMP) in the water quality model. As with the pollutant EMCs, independent sampling of effluent concentrations preserves the mean and standard deviation in the monitoring data.

- 3) <u>BMP Performance Irreducible Pollutant Effluent Concentrations</u>: When sampling from the lognormal distribution to estimate BMP performance with an effluent concentration it is possible to select values approaching or equal to zero. While well-functioning BMPs are capable of achieving high rates of pollutant removal, it is generally accepted that BMPs cannot completely remove pollutants from the water column. In effect BMPs, at best, can achieve what is called an "irreducible pollutant concentration" (Schueler, 1996). In an effort to prevent overestimating BMP performance in the model, lower limits were set for the effluent concentrations of each modeled pollutant and BMP as described in Section A.2.5.
- 4) <u>BMP Performance Limiting Pollutant Removal Estimates to Available Data:</u> Table A-16 and Table A-19 present model parameters used for estimating BMP pollutant effluent concentrations. Pollutant removal is only simulated for those pollutants, which have available data in the IBMPDB. In instances where data is not available for a parameter, no treatment is assumed for that parameter. This does not prevent the model from calculating load reductions of the pollutant as a result of volume reduction (i.e., hydrologic source control).
- 5) <u>BMP Performance BMPs are not a Source of Pollutants</u>: In instances when the randomly determined BMP effluent concentration exceeds the modeled influent concentration, no pollutant removal occurs and the effluent concentration is modified to equal the influent concentration. This prevents BMPs from acting as a source of pollutants in the water quality modeling. The commitment to regular and effective maintenance of the stormwater BMPs provides support for this assumption.

<u>Conclusions</u>: The above assumptions are expected to improve the accuracy of the water quality model estimates. The net result for the model outputs are somewhat conservative estimates of pollutant loads and concentrations due to estimation of model input parameters that are not compromised by the model methodology.

A.4. <u>Model Reliability</u>

Factors that affect model reliability include variability in environmental conditions and model error. To account for environmental variability, a statistical modeling approach was used that takes into account the observed variability in precipitation from storm to storm and from year to year. The model also takes into account the observed variability in water quality from storm to storm, and for different types of land uses. One way to express this variability is the coefficient of variation (COV) which is the ratio of the standard deviation of the variable to the mean value. Based on the statistical model, the range of COVs for annual pollutant loads was from 0.5 to 2.7 on an average annual basis, depending on the pollutant. This variability, or greater, is expected in typical storm water runoff, particularly for highly variable processes such as sediment load generation from open space watersheds.

Model error relates to the ability of the model to properly simulate the processes that affect storm water runoff, concentrations, and loads. Ideally model error is measured through calibration, but calibration is not feasible when considering a future condition. The model is a reasonable reflection of storm water processes because the model relies largely on measured regional data. For example, the runoff water quality data are obtained from a comprehensive monitoring program conducted by LA County that has measured runoff concentrations from a variety of land use catchments and for a statistically reliable number of storm events. In addition parameter estimation is fairly conservative resulting in moderately conservative estimates of changes in pollutant concentrations and loads.

A.5. References

ASCE/EPA (American Society of Civil Engineers Urban Water Resources Research Council and United States Environmental Protection Agency) 2003, International Stormwater Best Management Practices Database (www.bmpdatabase.org).

County of San Diego, 2003. San Diego County Hydrology Manual. Prepared by the County of San Diego Department of Public Works Flood Control Section. June 2003.

Devore, J.L., 1995. Probability and Statistics for Engineering and the Sciences. Fourth Ed. Brooks/Cole Publishing Co., Pacific Grove, CA.

DUDEK, 2015a. Memorandum, Cannon Road Project-DRAFT Preliminary Hydrology for Existing Condition. January 9.

DUDEK, 2015b. Proposed Land Use Plan. March 5.

Federal Highway Administration (FHWA), 1990. "Pollutant Loadings and Impacts from Stormwater Runoff, Volume III: Analytical Investigations and Research Report," Prepared by Woodward-Clyde Consultants: E.D. Driscoll, P.E. Shelley, and E.W. Strecker. FHWA-RD-88-008.

Geosyntec Consultants and Rick Engineering Company, 2014. Carlsbad Watershed Management Area Analysis. Prepared for San Diego County Permittees. October 3, 2014.

Helsel, D.R. and T. A. Cohn, 1988. "Estimation of descriptive statistics for multiply censored water quality data." *Wat. Resour. Res.* 24, 1997-2004.

Helsel, D.R. and Hirsch, R.M., 2002. *Statistical Methods in Water Resources*. U.S. Geological Survey, Techniques of Water-Resources Investigations Book 4, Chapter A3. Water Resources Division, USGS. Reston, VA

Hill, J., 2002. "Evaluation of Rational Method "C" Values". Prepared for San Diego County. June 2002.

Hirsch, R.M., and J. R. Stedinger 1987. "Plotting positions for historical floods and their precision," *Wat. Resour. Res.*, 23(4), 715-727

James, W. and R. C. James 2002. Hydrology: A Guide to the Rain, Temperature and Runoff, Combine and Statistics Modules of the USEPA SWMM4. Computational Hydraulics International, Ontario, Canada. October 2002.

Jennings, G., Line, D., Hunt, W., Osmond, D., and White, N., 2002. "Neuse River Basin Pollution Sources and Best Management Practices," Proceedings from the AWRA Specialty Conference on Coastal Water Resources, New Orleans, LA. www.bae.ncsu.edu/people/faculty/jennings/AWRA02_Jennings.htm

Los Angeles County (LA County), 1991. Los Angeles County Hydrology Manual, Department of Public Works, Alhambra, California, December.

Maidment, D.R. (ed.), Handbook of Hydrology. McGraw-Hill Inc., New York, NY (1993).

NRCS, 2013. Custom Soil Resource Report for San Diego County, California. http://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx

Royston, P. 1992. "Approximating the Shapiro-Wilk W test for Non-Normality." *Statistics and Computing*; 2:117-119.

Schueler, T., 1987. "Controlling Urban Runoff: A Practical Manual for Planning and Designing Urban BMPs," Publication No. 87703, Metropolitan Washington Council of Governments, Washington, DC.

Schueler, T. 1996. Irreducible Pollutant Concentrations Discharged from Urban BMPs. Watershed Protection Techniques, 1(3): 100-111. Watershed Protection Techniques 2(2): 361-363.

Shumway, R.H., Azari, R.S., and Kayhanian, M. 2002. "Statistical approaches to estimating mean water quality concentrations with detection limits." *Environ. Sci. Technol.* 36, 3345-3353.

Singh, A.K., A. Singh, and M. Engelhardt 1997. "The lognormal distribution in environmental applications." *EPA Technology Support Center Issue*, EPA 600-R-97-006.

Strecker, E., Quigley, M., Urbonas, B., Jones, J., and Clary, J., 2001. "Determining Urban Stormwater BMP Effectiveness," *Journal of Water Resources Planning and Management* May/June 2001.

Strecker, E.W., Quigley, M.M., Urbonas, B. and J. Jones., 2004. Analyses of the Expanded EPA/ASCE International BMP Database and Potential Implications for BMP Design, In Proceedings of the World Water and Environmental Resources Congress, Salt Lake City, Utah, American Society of Civil Engineers.

United States Environmental Protection Agency (USEPA), 1989. Analysis of Storm Event Characteristics for Selected Rainfall Gages throughout the United States, Prepared by Woodward-Clyde Consultants: E.D. Driscoll, G.E. Palhegyi, E.W. Strecker, and P.E. Shelley.

Water Environment Federation (WEF), 1998. WEF Manual of Practice No. 23/ASCE Manual of Practice No. 87, Urban Runoff Quality Management.